REMARKS/ARGUMENTS

This Amendment and Response is promptly filed to place the above-referenced case in condition for immediate allowance.

The status of the claims is as follows:

Cancelled:	1 - 6, 37 - 42, 45, 46, and 47;
Amended:	7, 17, 20, 25, 34, 43, and 44;
Added:	None; and
Currently outstanding:	7 - 24, 25 - 36, 43, and 44.

No new matter has been added to the application.

From the outstanding Office action, the Examiner rejected Claims 1-47 on a variety of bases including Sections 101, 102 and 103.

Applicants have amended their Claims to better set forth the subject matter of the present technology but reserve all right to pursue additional disclosure in the future.

Reconsideration is respectfully requested.

No narrowing amendment to conform with statute has been made in the Application by amendments to the claims, but instead the amendments are directed to further clarification of Applicants' technology.

In the outstanding Office Action, the Examiner indicated that certain items were missing from the Information Disclosure Statement filed September 5, 2003 (believed to be actually December 3, 2003). Enclosed herewith separately are copies of articles AE and AN from page 1 and AH from page 3. Article AC from page 1 is not yet available but it will be submitted as soon as made available.

The Examiner made certain claim objections to Claims 3, 17, and 43. These objections are believed to be resolved by the amendments to the claims.

The Examiner rejected certain of the claims under 35 USC § 101 as the claimed invention was considered by the Examiner to be directed to non-statutory subject matter. The amendments to the claims are believed to resolve this rejection by further clarification of Applicants' claimed subject matter. It is believed that the State Street case (149 F.3d 1368, 47 USPQ 2^{nd} 1596 (Fed.Cir.)) is applicable. Applicants particularly point out the utility of being able to provide date in a compressed form so that it occupies less storage space in a storage medium, electronic or otherwise. Furthermore, tangibility of Applicants' claimed invention is present in the testability, detectability, reliability, and controllability of the resulting compressed data as stored in a storage system.

The Examiner rejected several claims under 35 USC §112, first paragraph. The amendments to the claims are believed to resole these rejections.

Applicants have removed the term "3-dimensional video" from their claims. The term "energy" is generally known in the art with regards to intensity or other optical characteristics of a pixel, picture element, or image element. The term "intensity" is generally well-known in the art as is reflected by the Bright '977 patent. Applicants would generally be willing to revise their application to conform it with the vocabulary that is known in the art should it be deemed necessary.

The phrase "other learning regimes" has been removed from the claims.

Due to the foregoing, the rejections based on 35 USC §112, first paragraph are believed to be overcome.

The Examiner also rejected the claims based on 35 USC §102 and §103. Basically, for the claims as amended, the Bright '977 patent (Bright) is the basis for the Examiner's remaining objections.

Applicants believe that the Examiner has misinterpreted the Bright '977 patent and its relevance to the Yadegar et al compression method. The stark and fundamental differences between the Yadegar et al compression method and that due to the Bright '977 patent can be enumerated as below:

1. Yadegar et al apply tri-partite adaptive filtering method whereby;

1.1 Filter 1 treats the quasi-uniform regions in the image using on-line regression learning methods. In contrast, the Bright '977 patent offers an experimentally and theoretically verified inferior data-drive (non-learnable) method of linear interpolation method.

1.2 Filter 2 treats the piecewise extended and organized structures in the image using on-line and off-line adaptive non-linear regression learning methods. In contrast, the Bright '977 patent does not at all offer any method for treating piecewise extended organized structures.

1.3 Filter 3 treats the texture structures in the image using on-line and off-line adaptive non-linear regression learning methods to efficiently compress texture pattern. In contrast, the Bright '977 patent only suggests in brief passing a template matching method that requires large database of texture patterns and an extremely efficient search mechanism for texture pattern matching none of which are at all discussed in the Bright '977 patent.

2. Yadegar et al apply lossless adaptive on-line preconditioning/learning arithmetic coding to the residuals from Filter 1, Filter 2, and Filter 3 each separately for optimal last drop

compression. In contrast, in the Bright '977 patent there is no mention of lossless coding to the residuals.

Based on the above comparative analysis, the Bright patent can not act as disabling prior art to Applicants' claims. Applicants' claims go beyond that which is disclosed in the Bright '977 patent.

Furthermore, the addition of the Tsishkou et al. reference ("Tsishkou") does nothing to resolve the shortcomings of the Bright patent. As a result, all of Applicants' claims as amended are patentable over the Bright patent either alone or taken together with any reasonable combination of the cited references. Applicants believe that this extends also to any of the cited references taken in any reasonable combination in that none of them disclose Applicants' subject matter as claimed.

In order to better indicate their system, Applicants provide some additional descriptive material with regards to their system below.

Applicant' first filter decomposes the image into triangular tiles such as Peano-Cesaro tiling and applies on-line machine learning in the form of regression to each tile for modeling. The intention behind this stage of the algorithm is to capture quasi-uniform regions in the image using regression techniques. The algorithm appiles optimization methods to learn the most optimal model for intensity distribution over a tile in order for the approximation error to be below an error threshold.

The input to the regressor is not only the intensities at the vertices of the tile but also some intensities from neighboring tiles that are already modeled. This last extra information input to the regressor from neighboring tiles increases the likelihood of successful modeling.

If the tile is successfully modeled by Filter 1:

Declare tile terminal, which means do not consider it for further processing.

Go to the next tile.

Else if tile is not successfully modeled by Filter 1:

Decompose tile into subtiles.

Put subtiles in a priority queue data structure to be modeled later in the process.

Go to the next tile.

Applicants have conducted extensive experimentation on linear interpolation, linear regression and non-linear regression methods. Experiments strongly favor regression methods over liner interpolation, though for quasi-uniform regions the enhancements obtained by the application of non-linear regression over linear regression is small. For this reason Applicants have abandoned applying linear interpolation, which is the technique adopted by Bright, and have selected linear regression method over non-linear regression methods because of its computational efficiency. It is to be noted that Applicants have evidence from people working with them as well as documented evidence that their linear interpolation methods go back to the early 1990's.

By the time the algorithm is done with Filter 1, most of the quasi-uniform regions in the image frame have been captured and modeled. The remaining triangular tiles are medium range in size (about 17x17 pixels) and contain either (i) organized piecewise extended structures or (ii) texture, or (iii) combination of organized structures and texture. The intension behind this stage of Applicants' algorithm is for Filter 2 to model the organized piecewise extended structures in the image. Therefore, by the end of Filter 2 process, the

algorithm is left with texture, which may be interpreted as irratic and noisy strucutres. The texture region is then treated by the Filter 3 process.

For the Filter 2 process, Applicants have conducted extensive research and development applying adaptive structure modeling and machine learning methods to successfully model organized peicewise extended structures. The machine learning methods that Applicants have worked with, such as a mixture of Guassians, neural nets, Support Vector Machine (SVM), and Principle Component Analysis (PCA), can be considered as non-linear regression methods that have considerable learning power to learn and successfully model organized structures in medium size tiles.

Figure 6 exhibits some samples of piesewise extended structures.

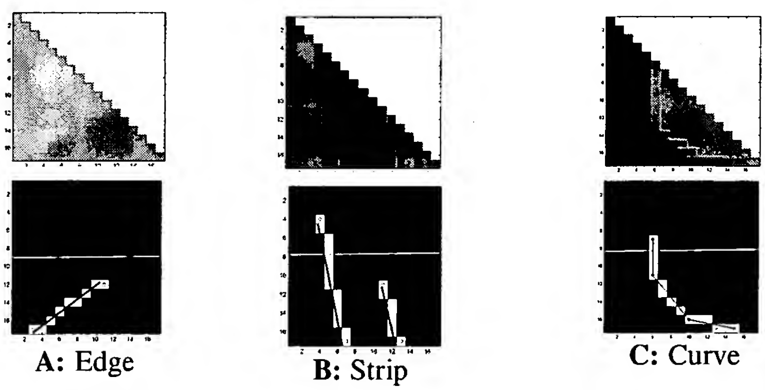

Figure 6

Filter 2 determines and traces the zero-crossing gradient regions in the tile. The blue traces in figure 6 are where zero-crossings take place.

The next step is to model the intensity distributions on either side of the zero-crossing traces bounded by a narrow strip of order 9 pixels in width using either on-line adaptive diffusion methods or off-line machine learning methods, either of which are highly non-linear regression by nature.

The final step in Filter 2 is to model the recessing, more or less quasi-uniform regions in the tile, which again is handled by either on-line adaptive or off-line machine learning methods.

If tile is successfully modeled by Filter 2:

Declare tile terminal, which means do not consider it for further processing.

Go to the next tile.

Else if tile is not successfully modeled by Filter 2:

Decompose tile into sub-tiles.

Put sub-tiles in a priority queue data structure to be modeled later in the process.

Go to the next tile.

The priority queue data structure used in Filter 2 inherently contains a sophisticated piece of strategy knowledge hardwired into its organization and processing. The tiles stored in the priority queue are ordered according to their likelihood of being successfully modeled if processed by Filter 2 mechanism. A tile has higher probability of success if a greater number of its neighboring tiles have already been successfully modeled, bearing in mind that a neighboring tile that has been modeled by Filter 2 mechanism offers more useful information due to the presence of piecewise extended structures in it than a neighboring tile modeled by Filter 1 mechanism due to the quasi-uniform distribution of intensities. Applicants have developed rigorous and extremely efficient algorithms to retrieve the complete set of neighboring tiles of a tile, which is a required step for Filter 2 processing. In the case of the Peano-Cesaro tiling in Figures 1 and 2, Applicants exploit the Peano-Cesaro sweep to establish a binary "state –labeling" or "code sequence" for the tiles as tile decomposition is applied. The

binary code sequence of a tile embeds an inheritance and relational knowledge about the tile to its parent, grandparents, ancestors, children, grandchildren, deeper generations of tiles, sibling and side and vertex adjacent tiles. Applicants pervasively exploit the binary code sequence in tile retrieval algorithms.

By the time the algorithm is done with Filter 2, most of the piecewise extended structures in the image frame have been captured and modeled. The remaining triangular tiles are small size (about 5x5 pixels or less) predominately containing texture patterns. The intention behind this stage of Applicants' algorithm is for Filter 3 to model texture as an extension of the non-linier filtration of Filter 2.

Therefore, by the end of Filter 3 process the algorithm is left to treat the residual information from Filter 1, Filter 2, and Filter 3 for the last drop compression using adaptive arithmetic coding.

If the piecewise "extended" structures are made "less and less extended" in their structural patterns, they become less and less differentiable and hence more and more noise like. For instance, consider an edge running for a good length of say 20 pixels, before changing direction to another lengthy edge as illustrated in Figure 7. Such a structure is piecewise extended and can be successfully modeled by Filter 2 mechanism in Stage 3 of Applicants' algorithm. Figure 8 illustrates the same structure as in Figure 7 but now the lengths of the subtended edges are much smaller, say about 3 pixels in length. Figure 9 depicts several corner structures such as those in Figure 8 entangled and crisscrossing each other in a region of the image. This entangled texture organization of intensity distribution as shown in Figure 9 is no longer piecewise extended structure and can no longer be handled by

Filter 2 mechanism. It is the responsibility of Filter 3 to model texture behavior such as in Figure 9.

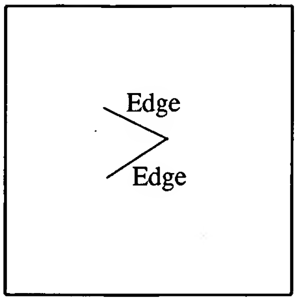

Figure 7

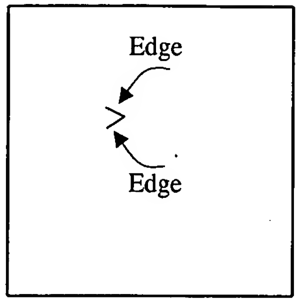

Figure 8

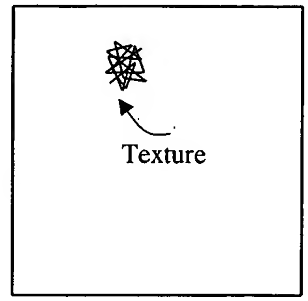

Figure 9

The analysis above on how in the limit piecewise extended structure become noise like and texture lead to the following important conclusion. Piecewise extended structures such as in Figure 7 preserve local invariance for a good extend length. Thus an edge in Figure 7 preserves the same gradient along the edge for some 20 pixels. This local invariance is of key significance to Filter 2 mechanism and the successful modeling of piecewise extended structures.

In stark contrast, texture behavior does not exhibit local invariance for, as Figure 9 illustrates, the gradient pattern keeps rapidly changing from one to the other. However, texture patterns to lesser or greater degree, depending on the particular texture, exhibit global correlation in their patterns. Thus in Figure 9 if the pattern of the crisscrosses spread over a region in the image, the global texture pattern reveals a global similarity that can be exploited for compression purposes and this is precisely what Applicants' Filter 3 does.

Applicants have done and continue to do extensive research and development in maturing and optimizing various algorithms for texture modeling. According to Yadegar et al, texture template matching is a poor and elementary method of modeling texture. Texture

template matching would require a large database of texture patterns to be kept in memory as part of the codec and it also requires an efficient real-time split-second search mechanism for optimal template matching. Applicants' generally do not follow texture matching.

Applicants have conducted and continue to conduct machine learning methods such as a mixture of Gaussians, inpainting methods and random field methods for texture modeling. All these methods at their core are adaptive and non-linear and they all attempt to off-line or on-line learn or adapt texture patterns at various localities in the image and fill in for (or inpaint) wider texture areas in the image using the learned or adapted texture samplings from various localities.

It is clearly the case that due to less correlation in information in a texture based region, the compression factors obtained in Filter 3 are less than those obtained in Filter 2. Indeed a statement can be made that the compression factors obtained from Filter 1 are greater than those obtained from Filter 2, which in turn is greater than those obtained from Filter 3.

The important point to bear in mind is that these compression factors from Filter 1, Filter 2 and Filter 3 have multiplicative (and not additive) effect on each other. Thus, for instance, compression factors of 15 (from Filter 1), and 3 (from Filter 2) and 1.3 (from Filter 3) will yield a global compression of order $15 \times 3 \times 1.3 \approx 58$ (and not $15 + 3 + 1.3 \approx 19$).

If tile is successfully modeled by Filter 3:

Declare tile terminal, which means do not consider it for further processing.

Go to the next tile

Else if tile is not successfully modeled by Filter 3:

Decompose tile into sub-tiles.

Put sub-tiles in priority queue data structure to be modeled later in the process.

Go to the next tile.

Applicants subject the residual information from Filter 1, Filter 2 and Filter 3 to adaptive arithmetic coding for last drop compression. However, before subjecting the residual information from Filter 2 to adaptive arithmetic coding, Applicants have observed that this residual information still maintains some consistency and correlation in piecewise extended structural forms. Experiments conducted have revealed that off-line or on-line machine learning or adaptive modeling can be further applied to this residual information by Filter 2 to further gain compression. As a result of this finding, the "first order residual" from Filter 2 goes into a second round of Filter 2 processing for further compression. The output of this second round of Filter 2 processing is the "second order residual" which is next subjected to adaptive arithmetic coding.

Adaptive arithmetic coding is an online learning/preconditioning mechanism for lossless coding. When this adaptive arithmetic lossless coding first starts the last drop compression of the residual information, it has no knowledge about the entropy of the residual information. As it penetrates into the stream of the residual information, it builds a probability distribution model of the stream that dynamically updates itself as the steam of residual information is processed. The probability model at each instance in the process assigns least code to the highest recurring residual pattern and follows that ranking throughout the processed portion of the residual stream. As mentioned, this probability model gets updated as the lossless arithmetic coding advances into the residual stream. By the time the process is complete and the residual stream is exhausted, the most optimal code assignment has been preconditioned.

Extensive experiments conducted by Applicants indicate that higher compression factors are achieved by keeping residuals from Filter 1, Filter 2 and Filter 3 separate. This is a natural conclusion, since Filter 1 deals with quasi-uniform regions and the residual from Filter 1 shows greater entropy consistency (that is, lower entropy) by keeping it separate than having it mixed with the residual from Filter 2, which deals with piecewise extended structures. Similar arguments apply to residuals from Filter 2 and Filter 3.

The Tsishkou et al publication describes an image compression algorithm that is suitable for a niche domain specific class of images such as ultrasound images of the heart. Therefore, the compression method is highly class based and it can not be exploited in a setting with generic images.

The core of the Tsishkou et al algorithm is composed of two parts: (i) the hierarchical database generation of templates of visual descriptors using a large training set of cardio ultrasound images and (ii) devising a two stage search mechanism for template matching to find the closest match in the database for run-time cardio ultrasound image compression application.

The Tsishkou et al algorithm shows wide divergence from Applicants' algorithm. Tsishkou et al algorithm is strongly class based whereas Applicants' algorithm can be made to be generic or class based depending on the specific application. Tsishkou et al algorithm requires off-line generation of a hierarchical database of indices whereas Applicants' algorithm requires on-line and off-line linear and non-linear regression machine learning regime whereby the internal parameters of the learning regime are tuned on the basis of the training set – this difference makes Applicants' method far more scalable. It is important to note that Applicants'

algorithm requires no database of templates of any sort, none whatsoever. Tsishkou et al algorithm requires construction of an explicit, extremely efficient search algorithm for template matching whereas Applicants' machine learning paradigm totally overcomes the search hurdle since, during training and adjustment of the internal parameter of the learning regime, a mapping is established between the training set and the output of the learning regime so that at run-time this mapping is spontaneously activated for a match. Tsishkou et al do not spell out any specific decomposition scheme: Whether triangular or rectangular? Binary, quaternary, ternary or what? The caption of Figure 1 in Tsishkou et al publication states segmentation based on polar coordinates. Yadegar et al's algorithms are not specific to polar or Cartesian coordinate systems and they have been applied to a variety of triangular decomposition techniques. Tsishkou et al do not spell out the specific lossless coding method other than stating that they apply entropy coding. Applicants have applied a variety of lossless coding methods such as differential coding, run length coding, Huffman coding, arithmetic coding and adaptive arithmetic coding. Applicants' experiments demonstrate adaptive arithmetic coding to be superior.

The Examiner has also cited a number of patents and publications as pertinent to the presently claimed invention. Since none of these have been relied upon as a reference against Applicants' claims, no further comment is deemed necessary.

In view of the above, the Examiner is respectfully requested to reconsider his position in view of the remarks made herein and the structural distinctions now set forth. The Examiner's rejections of the outstanding claims are believed to no longer apply. It is now believed that this application has been placed in condition for allowance, and such action is

respectfully requested. Prompt and favorable action on the merits is earnestly solicited. Applicants respectfully request that a timely Notice of Allowance be issued in this case.

The statements made herein with respect to the disclosures in the cited references represent the present opinions of the undersigned attorney. In the event that the Examiner disagrees with any of such opinions, it is respectfully requested that the Examiner specifically indicate those portions of the respective references providing the basis for a contrary view.

If the Examiner believes that a telephone or other conference would be of value in expediting the prosecution of the present application, enabling an Examiner's amendment or other meaningful discussion of the case, Applicants invite the Examiner to contact Applicants' representative at the number listed below.

With the above-referenced changes, it is believed that the application is in a condition for allowance; and Applicants respectfully request the Examiner to pass the application on to allowance. It is not believed that any additional fees are due; however, in the event any additional fees are due, the Examiner is authorized to charge Applicants' Attorney's Deposit Account No. 03-2030.

Respectfully submitted,

CISLO & THOMAS LLP

Date: August 11, 2006

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DMC/ASJ/sc
Enclosures
Petition for Extension of Time - 1 Month
Supplemental Information Disclosure Statement and Citation
Transmittal Letter with Fee Calculation
Acknowledgement Postcard

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